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A multi-criteria decision making method for urban flood resilience evaluation with hybrid uncertainties

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ABSTRACT

Urbanization and climate change have increased the frequency of damaging urban floods. While some urban floods are inevitable, it is critical to ensure urban flood resilience to minimize flood losses. This paper develops an urban flood resilience evaluation system that can provide guidance for municipal decision makers. This study first builds a comprehensive flood resilience evaluation system with the whole period of the disaster cycle that covers the resistance capacity before a flood, the coping and recovery capacities during a flood, and the adaptive capacity after a flood. The proposed evaluation system includes hybrid uncertain information that involves hesitant fuzzy judgements from experts and random data. Then, to conquer the weighting difficulty, a maximum consensus model for experts' weights is proposed. After that, the traditional VIKOR method is expanded to aggregate all crisp, random and hesitant fuzzy information, so that, the aggregation method is more adaptive to hybrid uncertain environment. In addition, the proposed method is applied to 5 south-eastern coastal cities in P.R.China. Practical managerial suggestions are put forward to increase urban flood resilience in these cities. Finally, the sensitivity analysis for the results and the comparison analysis are conducted.

1. Introduction

Urban floods has become a more common global problem in recent decades because of accelerating urbanization and climate change. In 2017, 38.4% of global natural disasters were floods [1], and without drastic strategies, annual global flood losses could reach $1 trillion by 2050 [2]. However, in many cities floods are inevitable, with many suffering from periodic floods [3,4]; therefore, it is necessary for these cities to have suitable flood resilience strategies [3]. The United Nations Office for Disaster Risk Reduction (UNISDR) Making Cities Resilient campaign has attracted more than 3800 cities [5], the UN Human Settlements Programme has resilience as its key strategy [6], and many decision makers and planners have adopted resilience improvements as a key operational goal [3].

As shown in Fig. 1, the concept of resilience dates back to the early 1970s when Holling proposed engineering and ecological resilience [7,8]. Holling defined engineering resilience as the ability to maintain a stable system state, and ecological resilience as the ability to transform to another stable state using mutually reinforcing structures [8]. In disaster management, urban flood resilience is a part of ecological resilience, which specifically refers to a multi-equilibria paradigm [4]. Resilience has been applied to social systems and coupled human-environment systems [7], such as urban drainage systems [9], green infrastructure systems [10] and community systems [11]. More recently, resilience has been developed into an integrated concept that covers all stages of the disaster management cycle. For disaster resilience in urban areas, specific quantification methods have been developed to translate these concepts into tangible, operational management practices.

System resilience measurements methods include both general and structure-based models, which respectively examine system performance and system structures [12]. The most common general models are the resilience triangle, a typical static performance-based model, and Bayesian probability, a dynamic performance-based model [7,11,13]. The resilience triangle uses integral equations in a static performance model to indicate system quality losses in the areas surrounding the system recovery and functionality curves in a coordinate graph [7,12]. Bayesian joint conditional probability, on the other hand, can be used to generate weights for the indicators in dynamic models [11,13]. There are 3 typical structure-based models [12]: simulation models, optimization models, and fuzzy logic models. Simulation

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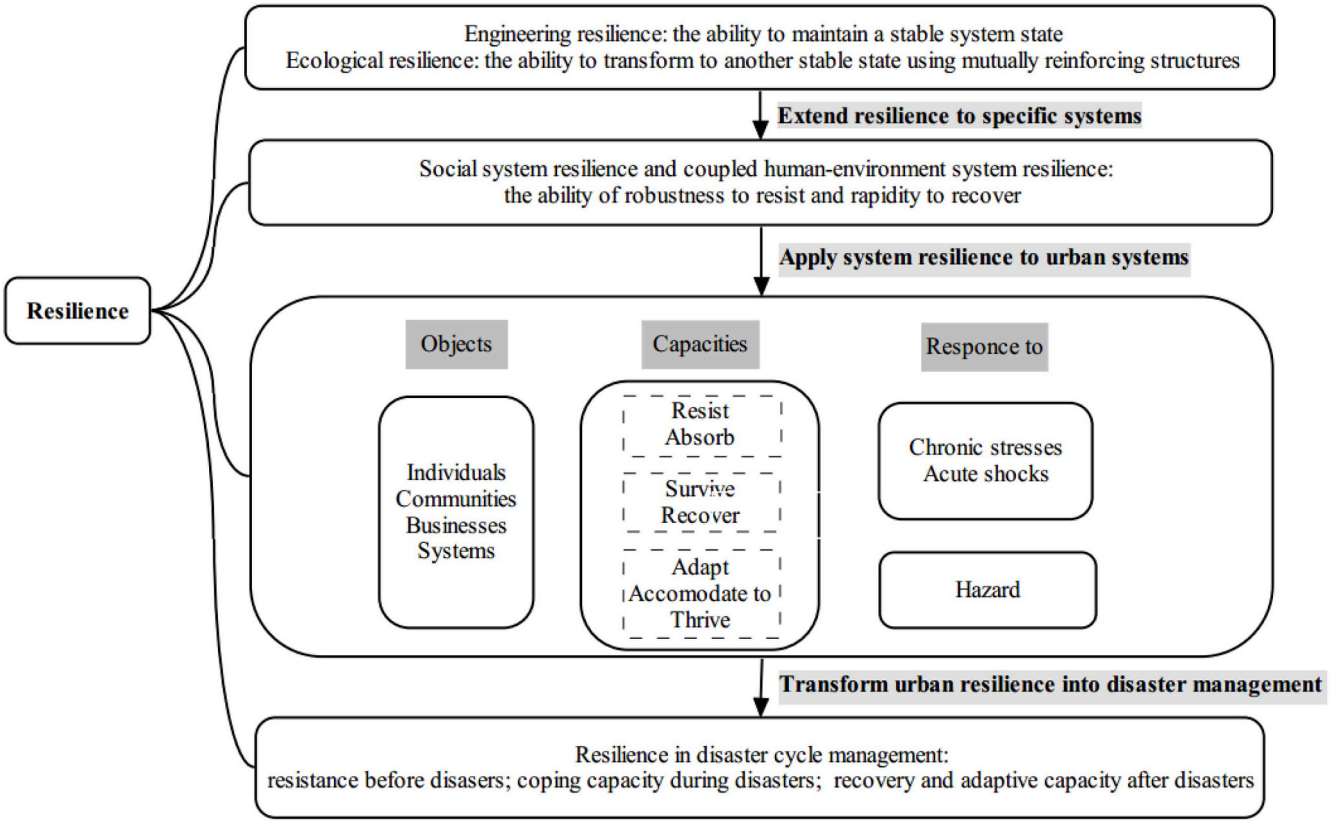

Fig. 1. The development of resilience.

models generally include geographic information system (GIS), three-dimensional (3D) visualization and Monte Carlo simulation information, with the combined GIS and 3D allowing for scenario descriptions and spatial analyses [11,14–16], and the Monte Carlo simulation being used to determine probability distributions for the evaluation system criteria and to model the uncertainty [17]. Multi-objective optimization models include combined indexes as its objectives and can be used to minimize flood damage and costs [18,19]. Fuzzy logic models are able to rank resilience factors and set scenarios at different vulnerability levels [3,20].

Although many studies have measured the urban flood resilience, most of them focused on the objective information and quantification analysis. The uncertainty of the information caused by the incomplete of the knowledge or the subjective information were ignored. For example, some experts' linguistic assessment were interval-valued terms and their black-or-white assessment information were not available because of the incomplete of the knowledge [55]. Among the previous methods for the resilience measurement, the probability was applied to handle the uncertainty of information in different models. For example, the GIS and 3D methods used the probability to simulate the scenarios. However, the uncertainty is not probabilistic but the vagueness [21]. Therefore the fuzzy set theory was developed and applied successfully to depict the imperfect, incomplete, and vague information. Nevertheless, there were limitations for the traditional fuzzy set theory when the information vagueness had different sources [22]. In the recent decades, hesitant fuzzy linguistic sets (HFLS) [46], developed from the hesitant fuzzy sets (HFS), were proposed to set all the possible values and express more flexible linguistic assessment information for the human beings' cognitive process. Through this way, the uncertainty and vagueness from the subjective hesitant information were decreased. Consequently, the urban flood resilience is a typical multi-criteria decision making problem with hybrid information, and it is necessary to consider both the objective indicators, such as the green space area rate and the population density, and the subjective indicators, such as the material resilience of floodgates.

Therefore, this paper first builds a comprehensive flood resilience evaluation system with the whole period of the disaster cycle, in which some indicators' information comes from experts' subjective assessments. However, it is difficult for experts to give judgements precisely. To handle the subjective vagueness, the hesitant fuzziness is employed to describe experts linguistic terms. Hence, hybrid crisp, random and hesitant fuzzy values are all included in the evaluation system. After that, a new information aggregation method is developed for the comprehensive flood resilience evaluation system. The main contributions of this paper are: (1) considering hesitant fuzziness in the urban flood resilience system evaluation for the first time, (2) improving equal experts' weights through a maximum consensus and minimum divergence model; and (3) updating the traditional VIKOR method to be sufficiently elastic to accommodate hybrid crisp, random and hesitant fuzzy values.

2. Key problem statement

2.1. Flood resilience under disaster cycle

Resilience is related to but different from *sustainability* and *vulnerability*. Sustainability emphasizes ordinary events that have a high probability and a low impact, while resilience deals with low probability extreme events that have a high impact [7,25]. Therefore, in flood management, sustainability is the maintenance of long-term stable system characteristics and resilience is the ability to deal with short-term dramatic conditions to avoid or reduce the damage from extreme floods; that is, resilience is closely related to sustainability [25,26], with diversification being a key resilience recovery capacity indicator [24]. Vulnerability is the propensity to be adversely affected by the sensitivity to harm and a lack of capacity to cope and adapt [27]. This definition indicates that

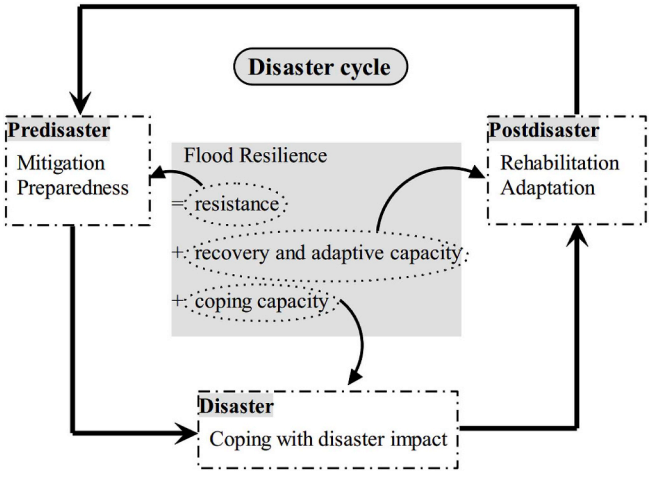

Fig. 2. Flood resilience under disaster cycle.

higher resilience means less vulnerability with opposite ends [28,29]. Under the disaster cycle, resilience emphasizes more on the resistance capacity before disasters, while vulnerability emphasizes more on the coping capacity and adaptive capacity during and after disasters. Besides, resilience studies uncertainty and dynamics in the system, which is beneficial in analyzing vulnerability in a more comprehensive way [29]. This study considers the opposite relationship between resilience and vulnerability, namely, the vulnerability indicators have negative effects on resilience.

As shown in Fig. 2, there are 4 main flood resilience capacities in the disaster cycle: pre-disaster resistance capacity, disaster coping capacity, and post-disaster recovery and adaptive capacities [3,6,18,30].

Pre-disaster *resistance* refers to the action taken before the next disaster or in the time between disasters [30] to prepare for a future flood with the key standard being to reduce as much as possible the negative effects of future floods. Therefore, this would involve resilience preparation capacity activities such as strengthening green infrastructure, urban drainage systems, and accurate forecasting and warning systems.

Coping capacity refers to the ability to avoid permanent damage, guarantee basic resources and services such as search and rescue and food and shelter. During this period, emergency awareness and the fundamental self-saving capacity of the people enhances the coping capacity.

The post-disaster *recovery* and *adaptive capacity* refer to the basic abilities needed for rehabilitation, as well as the ability to adapt through policy upgrading to increase future resilience, with social, economic, and education conditions being the main factors in the assessment process.

This paper builds an urban flood resilience evaluation system based on these four capacities.

2.2. Hybrid information

Urban flood resilience evaluation systems have hybrid information, some of which is crisp (eg. population size), some of which is random (eg. green space area rate), and some of which is hesitant and fuzzy (eg. material resilience level of floodgates).

As random values from out of control external factors are uncertain, determining the random indicators is difficult. Therefore, this paper uses the Monte Carlo method to simulate the fluctuating random values. According to the law of big numbers, as the number of experiments increases, the actual ratio of outcomes converge to the theoretical or expected ratio of outcomes. Using the Monte Carlo simulation and collected historical data, the number of experiments can be determined and the simulation distribution parameters obtained [31–34]. Therefore, the random values are equal to the expected simulation, which allows for the random values to be merged into crisp values.

For the other indicators, there is no exact measurement approach to determine the crisp or random values. For example, to assess floodgate resilience, information from thousands of floodgates is needed [2], which significantly increases the estimation difficulty. Therefore, in these types of situation, expert evaluation is used; however, as experts generally find it difficult to give crisp values or black-and-white judgements and forcing them to do so could compromise accuracy, they generally give a range within which they feel the value belongs. For example, in this case, urban disaster management experts would provide linguistic assessments for the hesitant fuzzy indicators from linguistic values that are generated as real numbers between 0 and 1 using a compatibility function [35–37]. For example, Li et al. [37] used a 7-scaled score model to characterize the linguistic values $\{E_{-3}, E_{-2}, E_{-1}, E_0, E_1, E_2, E_3\} = \{$*Extremely poor*, *Very poor*, *Poor*, *Medium*, *Good*, *Very good*, *Extremely good*$\}$ as real numbers {0, 0.17, 0.33, 0.5, 0.67, 0.83, 1}.

To deal with the hybrid information involving crisp, random and hesitant fuzziness, the traditional aggregation method has to be improved.

3. Urban flood resilience evaluation framework

3.1. Urban flood resilience evaluation indicator system

According to the disaster cycle mentioned in Section 2.1, the urban flood resilience evaluation indicator system can be divided into 4 subsystems as shown in Fig. 3: resistance, coping capacity, recovery, and adaptive capacity, which are respectively denoted by D_1, D_2, D_3 and D_4. The resistance (D_1) subsystem has two factors: green infrastructure (R_1), and warning and forecasting (R_2); the coping capacity (D_2) subsystem has three factors: hydrological infrastructure (R_3), population composition (R_4), and support resources (R_5); the recovery subsystem (D_3) has two factors: local economics (R_6), and social condition (R_7); and the adaptive capacity (D_4) subsystem has one factor: institutional learning mechanism (R_8). Selection of indicators is largely based on previous research about flood resilience indicators [2,10,11,39–42], and principles of indicators selection [44,45]:

(1) The consensus principle. The indicators need to be in consensus with the four capacities and the evaluation system logic.
(2) The standardization principle. The indicators need to be widely applicable to most cities so that the evaluation system can be applied to different systems to compare flood resilience levels.
(3) The convenience principle. The indicator values should be easy to obtain and manage to increase evaluation system universality.
(4) The integrity principle. The evaluation system should include 5 dimensions of urban flood resilience [38]: the natural, physical, economic, social, and institutional dimensions.

This system proposes two pre-disaster resistance capacity aspects: green infrastructure (R_1), and warning and forecasting (R_2). For pre-disaster resilience, Song et al. [39] suggested that green infrastructure could efficiently promote flood resilience and Tauhid et al. [43] also suggested that urban green infrastructure was related to climate-associated flood mitigation. Especially some urban campaigns including Sponge City building in China, Blue-green City building in UK, Water-sensitive urban design in Australian, and Low impact development, green infrastructure building and water system operation have been developed quickly. The mitigation capacity of the green infrastructure system need to be evaluated in the urban flood resilience system. Flood warning systems were a key to flood preparation and flood mitigation [40]. This evaluation system chooses several indicators surrounding to warning and forecasting system of the urban.

Emergency capacity is a vital coping capacity factor. As the physical

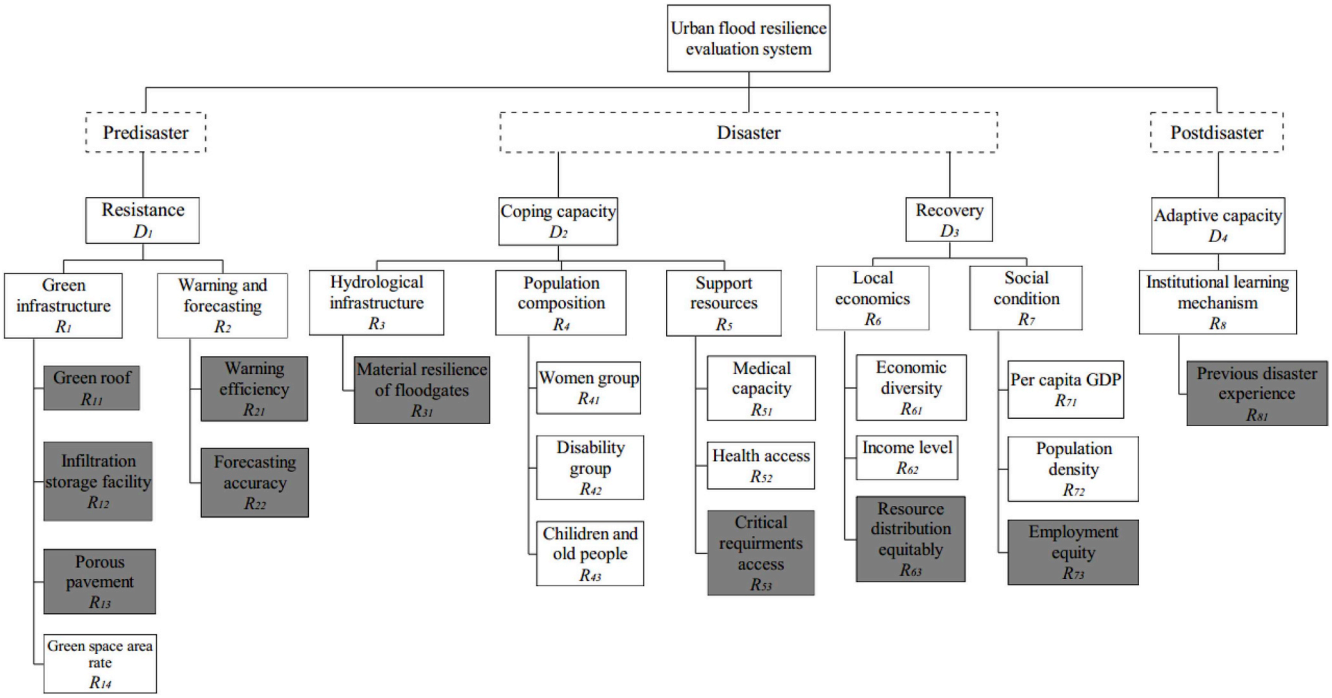

Fig. 3. Urban flood resilience evaluation system (Grey square frames indicate hesitant fuzzy indicators; white square frames indicate crisp and random indicators).

factor of urban flood resilience, the urban hydrological infrastructure (R_3) should be able to mitigate floods by coordinating water flows during a flood emergency to protect vulnerable groups. While drainage network parameters such as pipeline roughness are part of the green infrastructure, they can significantly influence the infiltration storage facility. Therefore, the framework in this paper only considers hydrological floodgate resilience for low repeatability. The second coping capacity factor is population composition (R_4), which focuses on vulnerable groups. The difficulty to rescue during the disasters is shown from this natural social factor. Hospitals are not only an emergency shelter but also directly affect the flood damage. Farley et al. [42] claimed that robust healthcare systems can strengthen flood and other disaster resilience. This evaluation system chooses the medical robustness, represented by support resources, as the second factor (support resources R_5) for the urban coping capacity.

In the post-disaster period, the recovery and adaptive capacities are related to the economic (R_6) and social conditions (R_7). The economic, equity, and institutional capacities need to be contained. For example, the 100 RESILIENCE CITIES campaign [64] proposed to strengthen the national flood insurance program, in which the action steps for legislative and executive are detail. The governments of different regions have different policies on disaster equity and insurance, therefore this evaluation system chooses the general factors to evaluate the economic level. For the institutional dimension (R_8), the linguistic indicators are chosen to evaluate the adaptive capacity. In summary, in this system, local economics, social conditions, and institutional learning mechanisms are considered.

Specifically, the rationality of indicators selection under $R_1 - R_8$ is stated in the following.

3.1.1. Resistance indicators

As a basic strategy for urban resilience, building green infrastructure allows for the conveyance and storage of floodwater [4]. Green infrastructure generally includes “green roofs, permeable pavements, bioretention cells, rain barrels, and vegetated swale” [10], and other green factors [39] such as soil and vegetation assistance in balancing surface water. Therefore, green infrastructure is able to mitigate negative flood effects and increase flood resistance. For the green infrastructure (R_1), this model considers four indicators: green roof (R_{11}), infiltration storage facility (R_{12}), porous pavement (R_{13}), and green space area (R_{14}).

Warning and forecasting (R_2) indicates the availability of precise forecasting and preparedness capacity. Warning efficiency (R_{21}) and forecasting accuracy (R_{22}) are two warning and forecasting indicators, which have hesitant fuzzy values. Timely and precise warning systems can ensure that the vulnerable populations are able to adequately prepare, which reduces possible future flood damage [40]. Forecasting accuracy (R_{22}), which is related to pre-disaster preparation, is related to a city's disaster forecasting capacity. Details of these hesitant fuzzy indicators are given in Table 1.

3.1.2. Coping capacity indicators

Floodgates are the main hydrological infrastructure used to control floodwater flows. A floodgate's resilience is the sum of its material resilience and the total resilience of the connected upstream floodgates. As the material resilience of a floodgate (R_{31}) [2] is related to its physical properties, there is no determined measurement method.

Coping capacity deals with a city's emergency capacity, with

Table 1
Description for hesitant fuzzy indicators.

Hesitant fuzzy indicators	Description
R_{11}	Popularity degree and implementation results of green roofs
R_{12}	Comprehensive infiltration storage facility level
R_{13}	Popularity degree and implementation results of porous pavement
R_{21}	Warning spreading from authority departments and inhabitant warning receptivity
R_{22}	Degree of forecasting accuracy

emergency response being closely related to group vulnerability. As group vulnerability increases emergency difficulty and negatively affects urban flood resilience, a higher coping capacity is needed because the more vulnerable the people, the less resilient the city. This model considers three population composition indicators females (R_{41}), the disabled (R_{42}), and children and old people (R_{43}).

The female indicator (R_{41}) is determined by the percentage of women vulnerable to the natural hazard (n_w) divided by the population of the city (n).

$$R_{41} = \frac{n_w}{n} \times 100\%. \tag{1}$$

Disability group (R_{42}) is calculated by the percentage of population with any kind of disability (n_d) divided by population of the city (n).

$$R_{42} = \frac{n_d}{n} \times 100\%. \tag{2}$$

The children and old people indicator (R_{43}) is the percentage of children under 15 (n_{15^-}) and the percentage of the population over 65 years of age (n_{65^+}).

$$R_{43} = \frac{n_{15^-} + n_{65^+}}{n} \times 100\%. \tag{3}$$

There are three support resource indicators: medical capacity (R_{51}), health access (R_{52}), and critical infrastructure access (R_{53}).

Medical capacity is calculated as the number of hospitals per 1000 population and is denoted by h.

$$R_{51} = \frac{h \times 1000}{n}. \tag{4}$$

Health access is calculated as the number of physicians per 1000 population and is denoted by n_p.

$$R_{52} = \frac{n_p \times 1000}{n}. \tag{5}$$

The critical requirements access indicator [11], R_{53}, is a hesitant fuzzy indicator. During a flood emergency, urban operations such as food, energy, and transportation [11] should satisfy the basic demands of the people.

3.1.3. Recovery indicators

Economic conditions and resource distribution react positively to rebuilding and rehabilitation after a flood. In this model, two indicators are used to measure economic conditions: economic diversity (R_{61}) and income level (R_{62}). The economic diversity equality entropy index [41] measures economic diversity, in which t is the number of sectors, and r_i is the share of economic activities in the industry. The higher the entropy index, the higher the economic diversity, and the higher the disaster and urban flood resilience [41]. Resource distribution equity (R_{63}) is a hesitant fuzzy indicator.

$$R_{61} = -\sum_{i=1}^{t} r_i \ln(r_i). \tag{6}$$

There are three indicators to measure the social condition (R_7); per capita GDP (R_{71}), population density (R_{72}), and employment equity (R_{73}). Household size is taken as the average household size, s, and population density is determined by the total population per area; that is, population size n divided by urban area a.

3.1.4. Adaptive indicators

The adaptive subsystem has one factor; institutional learning mechanism, R_8; the indicator for which R_{81} is used to assess previous disaster experiences. Proactive governments tend to have higher adaptive capacity. Generally, investment in infrastructure and transforming a disaster experience into policies are used to evaluate the adaptive capacity of urban governments.

3.2. VIKOR aggregation method

This paper chooses the VIKOR as the aggregation method for the following reasons: (1) VIKOR decreases the difficulty of the normalization for criteria with different units [47]; (2) the compromise solution obtained by VIKOR considers not only the maximize group utility but also the minimum individual regret [51]. Compared with TOPSIS, which only considers the distances between each alternatives to the ideal and negative-ideal solutions [44,52], VIKOR considers the relative importance of both two distances. As a result, the best alternative from VIKOR must be the closest one to the ideal solution [47]; (3) VIKOR method can obtain the ranking results based on the decision makers' preference between the group utility and the individual regret [48]. Through this way, the results are more flexible with the consideration of the preference of decision makers. The VIKOR method assists in finding compromise solutions to multi-criteria decision making problems that have conflicting criteria sets [48], and has recently been extended to a fuzzy VIKOR that is able to deal with triangular fuzzy values [49] and trapezoidal fuzzy numbers [50].

However, the traditional VIKOR method cannot handle hybrid uncertain information. Therefore, this paper extends the traditional VIKOR and uses the extended VIKOR method to deal with the hybrid crisp, random, and hesitant fuzzy information. Several research have extended the traditional methods for MCDM problems from the quantification analysis of all crisp data to the assessment values in a hesitant fuzzy environment. For example, Gitinavard et al. [23] proposed the hesitant fuzzy hierarchical TOPSIS method. Borujeni et al. [22] used an imprecise last aggregation preference selection index method and obtained the solution by the simultaneous application of HFS and preference relations. Besides, interval-valued hesitant fuzzy sets were widely operated in the decision making and weighting methods [53,54].

In the hybrid VIKOR model, $A_i (i = 1,2,\cdots,m)$ represents alternatives and $C_j (j = 1,2,\cdots,n)$ represents the criteria for each alternative. x_{ij} denotes the crisp indicators, j in the crisp set J_C; $\tilde{x}_{ij}$ denotes the hesitant fuzzy indicators, j in the hesitant fuzzy set J_H, with l_{ij} denoting the length of hesitant fuzzy indicators $\tilde{x}_{ij}$.

Step 1. Determine experts' weights ω^E. The expert weights are determined by minimizing the divergence in the expert evaluations and maximizing the group evaluation consensus [44,55]. This paper applies the following fuzzy Euclidean-distance-based model to minimize the sum of hesitant fuzzy ratings distances between two experts to determine experts' weights [55]:

$$\min_{\omega_p^E} D = \sum_{i=1}^{m} \sum_{j \in J_H} \sqrt{\frac{1}{L} \sum_{l=1}^{L} \sum_{p=1}^{g} \sum_{q=1, q \neq p}^{g} \left(\omega_p^E f_{p,ij} - \omega_q^E f_{q,ij}\right)^2} \tag{7}$$

s. t.

$$\begin{cases} f_{p,ij} = \left\{ f_{p,ij}^l | l = 1,2,\cdots,L,\ p = 1,2,\cdots,g,\ j \in J_H,\ i = 1,2,\cdots,m \right\}, \\ f_{q,ij} = \left\{ f_{q,ij}^l | l = 1,2,\cdots,L,\ q = 1,2,\cdots,g,\ q \neq p,\ j \in J_H,\ i = 1,2,\cdots,m \right\}, \\ \sum_{p=1}^{g} \omega_p^E = 1, \\ \omega_p^E,\ \omega_q^E \geq 0,\ p,\ q = 1,2,\cdots,m, \end{cases} \tag{8}$$

where $f_{p,ij}^l$ represents the lth number in the hesitant fuzzy judgement of the pth expert evaluating the $C_j (j \in J_H)$ for alternative A_i. As this model is able to calculate the minimum Euclidean-distances between each expert pair, maximum consensus is achieved and the expert weights $\omega^E = \{\omega_1^E, \cdots, \omega_p^E, \cdots, \omega_g^E\}$ are determined.

Step 2. Determine the criteria weight ω^C. The weighted average operator method for hesitant fuzzy environment [55] is applied to determine the criteria weights. First, the original hesitant fuzzy numbers z_{pj} is applied to determine the criteria weights. Then, the original hesitant fuzzy numbers z_{pj} into the same length, L [37]. The expert weights are then applied to these extended hesitant fuzzy numbers so that $\tilde{z}_{pj} = \{\omega_p^E z_{pj}^l | l = 1,2,\cdots,L,\ p = 1,2,\cdots,g,\ j = 1,2,\cdots,n\}$, where z_{pj}^l denotes the lth number in z_{pj}. Third, the weighted average operator method is applied to determine the parameters for each hesitant fuzzy judgement, $(\mu_j, \nu_j, \pi_j)(j \in J_C \cup J_H)$, as follows.

$$\begin{cases} \mu_j = \sum_{p=1}^{g} \tilde{z}_{pj}^1, \\ \nu_j = \sum_{p=1}^{g} \frac{1}{L-2}(\tilde{z}_{pj}^2 + \tilde{z}_{pj}^3 + \cdots + \tilde{z}_{pj}^{L-1}), \\ \pi_j = \sum_{p=1}^{g} \tilde{z}_{pj}^L. \end{cases} \tag{9}$$

Finally, the criteria weight $\omega^C = \{\omega_j^C | j \in J_C \cup J_H\}$ are obtained as this:

$$\omega_j^C = \frac{\mu_j + \pi_j\left(\frac{\mu_j}{\mu_j + \nu_j}\right)}{\sum_{j=1}^{n}\left[\mu_j + \pi_j\left(\frac{\mu_j}{\mu_j + \nu_j}\right)\right]}. \tag{10}$$

Step 3. Construct the hesitant fuzzy decision matrix D, and normalize the decision matrix.

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & \cdots & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} x_{11} & \cdots & \tilde{x}_{1j} & \cdots & \tilde{x}_{1n} \\ x_{21} & \cdots & \tilde{x}_{2j} & \cdots & \tilde{x}_{1n} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ x_{m1} & \cdots & \tilde{x}_{mj} & \cdots & \tilde{x}_{mn} \end{pmatrix} \end{array} \tag{11}$$

In this decision matrix, x_{ij} denotes the crisp indicators and random indicators, where random values are the expected values of indicator distributions as explained in Sec.2.2.

$$\tilde{x}_{ij}^l = \left\{ \sum_{p=1}^{g} \omega_p^E f_{p,ij}^l | l = 1,2,\cdots,L,\ i = 1,2,\cdots,m,\ j \in J_H \right\},$$

denotes to the hesitant fuzzy indicators. Let $g_{ij}, j \in J_C$ and $\tilde{g}_{ij}, j \in J_H$ respectively denote to the vector normalization for indicator J_C and J_H; then, the normalized decision matrix N is obtained, as follows:

$$N = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccccc} C_1 & \cdots & C_2 & \cdots & C_n \end{array} \\ \begin{pmatrix} g_{11} & \cdots & \tilde{g}_{1j} & \cdots & \tilde{g}_{1n} \\ g_{21} & \cdots & \tilde{g}_{2j} & \cdots & \tilde{g}_{1n} \\ \vdots & \cdots & \vdots & \cdots & \vdots \\ g_{m1} & \cdots & \tilde{g}_{mj} & \cdots & \tilde{g}_{mn} \end{pmatrix} \end{array} \tag{12}$$

where

$$g_{ij} = \left\{ \frac{g_{ij}}{\sqrt{\sum g_{ij}^2}} | i = 1,2,\cdots,m,\ j \in J_C \right\},$$

and

$$\tilde{g}_{ij}^l = \left\{ \frac{\tilde{g}_{ij}^l}{\sqrt{\sum \tilde{g}_{ij}^{l2}}} | l = 1,2,\cdots,L,\ i = 1,2,\cdots,m,\ j \in J_H \right\}.$$

Step 4. Calculate the Manhattan distance. $\tilde{g}_j^+$ is the maximum benefit criteria, which is positively related to the system goal, and while for, and $\tilde{g}_j^-$ is the minimum cost criteria, which is negatively related to the system goal. Based on the parameters $\varepsilon(\tilde{g}_{ij})$ and $\xi(\tilde{g}_{ij})$, hesitant fuzzy numbers can be ordered. These two parameters are calculated as follows. If $\varepsilon(\tilde{g}_1) < \varepsilon(\tilde{g}_2)$, then $\max\tilde{g}_i = \tilde{g}_2$, $\min\tilde{g}_i = \tilde{g}_1$; If $\varepsilon(\tilde{g}_1) = \varepsilon(\tilde{g}_2)$, $\xi(\tilde{g}_1) < \xi(\tilde{g}_2)$, then $\max\tilde{g}_i = \tilde{g}_1$, $\min\tilde{g}_i = \tilde{g}_2$; If $\varepsilon(\tilde{g}_1) = \varepsilon(\tilde{g}_2)$, $\xi(\tilde{g}_1) = \xi(\tilde{g}_2)$, then $\max\tilde{g}_i = \min\tilde{g}_i = \tilde{g}_1 = \tilde{g}_2$. Following this principle [48], $\tilde{g}_j^+$ and $\tilde{g}_j^-$ are obtained.

$$\varepsilon(\tilde{g}_{ij}) = \frac{1}{L}\sum_{l=1}^{L} \tilde{g}_{ij}^l, \tag{13}$$

$$\xi(\tilde{g}_{ij}) = \frac{1}{L} \sum_{\tilde{g}_{ij}^l, \tilde{g}_{ij}^{l'} \in \tilde{g}_{ij}} \sum_{l=2}^{l_{ij}} \left(\tilde{g}_{ij}^l - \tilde{g}_{ij}^{l'2} \right). \tag{14}$$

Compare $\tilde{g}_{ij}$ to determine $\tilde{g}_j^+ = \max\{\tilde{g}_{ij} | i = 1,2,\cdots,m\}$ and $\tilde{g}_j^- = \min\{\tilde{g}_{ij} | i = 1,2,\cdots,m\}$ for each benefit-type criterion. Following the same rule, g_j^+ and g_j^- are also determined. The opposite rule for cost-type criterion is followed, $\tilde{g}_j^+ = \min\{\tilde{g}_{ij} | i = 1,2,\cdots,m\}$ and $\tilde{g}_j^- = \max\{\tilde{g}_{ij} | i = 1,2,\cdots,m\}$. In the hesitant fuzzy VIKOR method, Manhattan distance is used to deffuzify all hesitant fuzzy values $\tilde{g}_{ij}$ to crisp distances $d\left(\tilde{g}_{ij}, \tilde{g}_j^+\right)$.

$$d\left(\tilde{g}_{ij}, \tilde{g}_j^+\right) = \frac{1}{L}\sum_{l=1}^{L} |\tilde{g}_{ij}^l - \tilde{g}_j^{+l}|. \tag{15}$$

Using this equation, $d\left(\tilde{g}_j^+, \tilde{g}_j^-\right)$ are also obtained.

For the crisp indicators, the values of the alternatives are ordered for each criterion. After determining the $\max g_{ij}$ and $\min g_{ij}$,

$$d\left(g_{ij}, g_j^+\right) = |g_{ij} - g_j^+|,\ i = 1,2,\ \cdots, m,\ j = 1,2,\ \cdots, n$$

and

$$d\left(g_j^+, g_j^-\right) = |g_j^+ - g_j^-|,\ i = 1,2,\ \cdots, m,\ j = 1,2,\ \cdots, n$$

are also calculated.

Step 5. Determine the group utility, S_i, and the individual regret R_i. The benefit criteria formulations are as follows, with the cost criteria using opposite formulations.

$$S_i = \sum_{j \in J_H} \frac{\omega_j^C d\left(\tilde{g}_{ij}, \tilde{g}_j^+\right)}{d\left(\tilde{g}_j^+, \tilde{g}_j^-\right)} + \sum_{j \in J_C} \frac{\omega_j^C d\left(g_{ij}, g_j^+\right)}{d\left(g_j^+, g_j^-\right)}, \tag{16}$$

$$R_i = \max_j \frac{\omega_j^C d\left(\tilde{g}_{ij}, \tilde{g}_j^+\right)}{d\left(\tilde{g}_j^+, \tilde{g}_j^-\right)}, j \in J_H, \tag{17}$$

$$R_i = \max_j \frac{\omega_j^C d\left(g_{ij}, g_j^+\right)}{d\left(g_j^+, g_j^-\right)}, j \in J_C. \tag{18}$$

Calculate $S^* = \min S_i$, $S^- = \max S_i$, $R^* = \min R_i$, $R^- = \max R_i$ for the following hesitant fuzzy compromise measurement. To ensure the validation of Q value, $S^- \neq S^*$ and $R^- \neq R^*$ should be simultaneously satisfied. The criteria need to be meaningful to avoid the same utility or the same regret. When the situation occurs, the specific Q value [56] will be applied. If $S^- = S^*$, Q should be modified as $\frac{R_i - R^*}{R^- - R^*}$. If $R^- = R^*$, Q should be modified as $\frac{S_i - S^*}{S^- - S^*}$. When both utility and regret values are the same, the VIKOR method can not deal with this.

Step 6. Determine ν and Q_i. ν is the weight to the strategy which maximizes utility for whole evaluation system. The larger, the smaller preference differences among criteria. Without loss of generality, ν takes 0.5. Q_i is calculated by the sum of distances for group utility and

individual regret; the better the alternative, the smaller Q_i.

$$Q_i = \frac{v(S_i - S^*)}{S^- - S^*} + \frac{(1-v)(R_i - R^*)}{R^- - R^*}. \quad (20)$$

Step 7. Rank S_i, R_i, Q_i, and determine the compromise solution.

The compromise solutions A_i should simultaneously satisfy these two conditions.

Condition 1. The alternative A_i simultaneously satisfies $S_{\bar{1}}$ and $R_{\bar{1}}$, showing that A_i has the smallest S and R. Let $\bar{\cdot}$ denote the order number; that is, $S_{\bar{w}}$, $w = 1,2, \cdots, W$, where W is the wth smallest of all S_i for alternative i, and $R_{\bar{v}}$, $v = 1,2, \cdots, V$, where V is the vth smallest of all R_i for alternative i.

$$S_{\bar{1}} < S_{\bar{2}} < \cdots < S_{\bar{W}}, R_{\bar{1}} < R_{\bar{2}} < \cdots < R_{\bar{V}}. \quad (21)$$

Condition 2. Rank the Q_i; so, $Q_{\bar{1}} < Q_{\bar{2}} < \cdots < Q_{\bar{Z}}$,

$$Q_{\bar{2}} - Q_{\bar{1}} \geq \frac{1}{m-1}. \quad (22)$$

If Condition 1 is not satisfied, then both $A_{\bar{1}}$ and $A_{\bar{2}}$ are compromise solutions. If Condition 2 is not satisfied, then all the alternatives A_i with $Q_{\bar{z}} - Q_{\bar{1}} < \frac{1}{n-1}$ are compromise solutions.

In conclusion, this proposed VIKOR information aggregation method has extended the traditional VIKOR on these aspects. First, this method applies the hesitant fuzziness to allow the experts assess linguistic variables by different linguistic terms, which reduces the subjective fuzziness of the experts' assessments. Second, the experts' weights are obtained through the proposed minimum divergence model. Compared to the artificially given weights in the traditional VIKOR, this model increases the maximum group consensus and improves the reliability of the results. Third, this proposed method extends the traditional VIKOR method to be sufficiently elastic to accommodate hybrid crisp and hesitant fuzzy information. In addition, for the different types of fuzzy sets, the attitude preference method is also applied to extend the linguistic hesitant fuzzy sets into the same length, which helps decrease the difficulties of information aggregation.

4. Case study

4.1. Case description

The urban flood resilience evaluation model was applied to 5 Chinese coastal cities: Guangzhou (A_1), Fuzhou (A_2), Ningbo (A_3), Shanghai (A_4), and Nanjing (A_5); all of which are located on the coastal areas in south-east China. Shanghai is a municipality directly under the Central Government, and the other four cities are provincial capitals; however, all are characterized by high urbanization, rapid economic development, and high flood frequencies.

Guangzhou is located in the Pearl River Delta area, which has experienced a rapid urban-rural integration process, and in which the city's GDP accounts for around 70% of Guangdong province's GDP. Guangzhou hosts the China Import and Export Commodities Fair and other trade projects, and high commerce turnover stimulates the economic development in Guangdong Province. Due to it highly developed water system and its coastal location, Guangzhou has a high flood risk, especially from rainstorms. Guangzhou's average rainfall for May and June is over 325 mm, significantly higher than in other months of the year. In June 2018, Guangzhou experienced a 21 h rainstorm, which resulted in the waterlogging of 34 roads, which in turn caused paralysis in the city's transportation network. A similar situation also occurred in Fuzhou in May 2015, after a 4 h rainstorm caused flooding in the city, bringing traffic to a standstill and severely testing the city's flood defensive management. Ningbo city authorities have paid close attention to disaster management, and invested around 51 million CNY to purchase catastrophe insurance worth 700 million CNY, which included disaster insurance and public security incident insurance. Shanghai is China's financial center and is also a key transportation hub; however, as it is located on the middle and lower reaches of the Changjiang River near the Taihu watershed, it experiences both heavy rainstorms and floods from Taihu watershed. Nanjing also faces a similar flood risk; for example, on July 2018, Nanjing's tidal level was 0.35 m beyond the warning line. Therefore, because these 5 Chinese cities face periodic or annual flood risks, they all need to be able to accurately assess their urban flood resilience levels.

The urban flood resilience evaluation system has hybrid crisp and hesitant fuzzy information. In this evaluation system, some indicators can not be assessed by precise numbers, such as the institutional learning mechanism of one city. Therefore, the expert evaluation is used for these indicators. To avoid to force experts to provide black-or-white or precise assessments, the hesitant fuzziness is applied to deal with this problem. Hesitant fuzziness allows the experts to provide several linguistic assessments. Through this way, the application of hesitant fuzziness increases the flexibility of experts' assessments. This paper also applies the proposed method to deal with the hybrid crisp and hesitant fuzzy information for 5 coastal cities in China.

4.2. Computations

Data in Table 2 were extracted from the Guangzhou Statistical Yearbook [57], Fuzhou Statistical Yearbook [58], Ningbo Statistical Yearbook [59], Shanghai Statistical Yearbook [60], Nanjing Statistical Yearbook [61]. The green space area rate of Ningbo and Fuzhou were extracted from the information in the websites of Ningbo City Garden [62] and Fuzhou Government [63]. The data were collected in December 2018. The 5 experts were from the disaster management departments. The original crisp information were shown in Table 2 and the hesitant fuzzy terms were shown in Table 3.

As the urban flood resilience evaluation system model, the crisp and random indicators were $J_C = \{14,41,42,43, 51,52,61,62,71,72\}$, and the hesitant fuzzy indicators were $J_H = \{11,12,13,21,22,31,53,63,73,81\}$. Five urban disaster management experts evaluated the hesitant fuzzy indicators in terms of criteria importance, with the expert criteria weights for J_H, being determined using model $(13-14)$ as follows, $\omega_p = \{0.195680728, 0.201661819 , 0.20277583, 0.199957506, 0.199924116\}$. Using the attitude-neutral extension, the expert criteria importance judgements were extended to the same length; therefore, the criteria weights were ω_j^C, $j \in J_C \cup J_H$ (Table 4).

As described in Step 3, normalize the crisp and hesitant fuzzy information through $\frac{g_{ij}}{\sqrt{\sum g_{ij}^2}}$ for $j \in J_C$ and $\frac{\tilde{g}_{ij}^l}{\sqrt{\sum \tilde{g}_{ij}^{l2}}}$ for $j \in J_H$. The normalized decision matrix N was then determined (Table 5, Table 6).

The urban flood resilience evaluation system cost-type indicators were $\{R_c\} = \{R_{41}, R_{42}, R_{43}, R_{72}\}$, and the benefit-indicator types were

Table 2
Case data for J_C.

	A_1	A_2	A_3	A_4	A_5
R_{14}	41.80%	48.00%	36.53%	38.30%	45.00%
R_{41}	51.83%	47.69%	50.40%	48.50%	48.20%
R_{42}	5.26%	5.67%	4.67%	4.09%	5.30%
R_{43}	18.14%	22.70%	20.30%	18.74%	18.70%
R_{51}(per 1000 people)	9.801	4.761	4.602	5.534	6.235
R_{52}(per 1000 people)	5.23	145.04	60.47	103.80	119.80
R_{61}	0.5153	0.8820	0.8168	0.9782	0.7707
R_{62}(RMB per month)	4811	3605	4587	6378	4620
R_{71}(RMB per capita)	224556.74	89386.52	108513.30	122413.96	126011.04
R_{72}(square meter per 1000 people)	0.8280	1.7261	1.2262	0.2754	0.7915

Table 3
Case data for.J_H.

J_H	Alternatives	z_1	z_2	z_3	z_4	z_5
R_{11}	A_1	(0.5, 0.67, 0.83)	(0.83)	(0.5, 0.67)	(0.5, 0.67)	(0.67)
	A_2	(0.67, 0.75, 0.83)	(0.67)	(0.5, 0.67)	(0.5)	(0.67)
	A_3	(0.5)	(0.33, 0.5, 0.67)	(0.5)	(0.67)	(0.33, 0.5)
	A_4	(0.67)	(0.5, 0.67, 0.83)	(0.5, 0.67)	(0.5, 0.67)	(0.67, 0.75, 0.83)
	A_5	(0.67, 0.75, 0.83)	(0.67)	(0.67)	(0.83)	(0.5, 0.67, 0.83)
R_{12}	A_1	(0.5, 0.67)	(0.33, 0.5, 0.67)	(0.5)	(0.67)	(0.67, 0.75, 0.83)
	A_2	(0.67, 0.75, 0.83)	(0.5, 0.67, 0.83)	(0.67)	(0.83)	(0.67, 0.75, 0.83)
	A_3	(0.67, 0.75, 0.83)	(0.5, 0.67)	(0.67)	(0.67, 0.75, 0.83)	(0.5)
	A_4	(0.67)	(0.5)	(0.5, 0.67)	(0.33, 0.5)	(0.67)
	A_5	(0.67, 0.75, 0.83)	(0.83)	(0.67)	(0.83)	(0.5, 0.67)
R_{13}	A_1	(0.5)	(0.33, 0.5)	(0.33)	(0.33, 0.5, 0.67)	(0.33)
	A_2	(0.33, 0.5)	(0.5, 0.67)	(0.67)	(0.5)	(0.67)
	A_3	(0.33)	(0.5)	(0.33)	(0.33, 0.5)	(0.5)
	A_4	(0.5, 0.67)	(0.33, 0.5, 0.67)	(0.5)	(0.33, 0.5)	(0.67)
	A_5	(0.67)	(0.5, 0.67)	(0.5)	(0.5)	(0.67)
R_{21}	A_1	(0.33, 0.5)	(0.33, 0.5)	(0.33)	(0.33, 0.5)	(0.5)
	A_2	(0.5, 0.67)	(0.5, 0.67)	(0.67)	(0.67)	(0.67, 0.75, 0.83)
	A_3	(0.83)	(0.67, 0.75, 0.83)	(0.67, 0.75, 0.83)	(0.5, 0.67)	(0.67, 0.75, 0.83)
	A_4	(0.5)	(0.33, 0.5, 0.67)	(0.33, 0.5)	(0.33, 0.5, 0.67)	(0.5)
	A_5	(0.5)	(0.67)	(0.5, 0.67)	(0.5, 0.67)	(0.67)
R_{22}	A_1	(0.5)	(0.33, 0.5, 0.67)	(0.33)	(0.33)	(0.5)
	A_2	(0.5, 0.67)	(0.5)	(0.5, 0.67, 0.83)	(0.67, 0.75, 0.83)	(0.67)
	A_3	(0.83)	(0.67, 0.75, 0.83)	(0.83)	(0.5, 0.67)	(0.67, 0.75, 0.83)
	A_4	(0.33, 0.5)	(0.5)	(0.5, 0.67)	(0.33, 0.5, 0.67)	(0.5)
	A_5	(0.5, 0.67)	(0.5)	(0.67)	(0.5, 0.67)	(0.67)
R_{31}	A_1	(0.67, 0.75, 0.83)	(0.5, 0.67)	(0.33, 0.5, 0.67)	(0.5)	(0.67)
	A_2	(0.33, 0.5, 0.67)	(0.5)	(0.5, 0.67)	(0.67)	(0.5)
	A_3	(0.33, 0.5)	(0.5)	(0.5, 0.67)	(0.5)	(0.5)
	A_4	(0.5)	(0.5, 0.67, 0.83)	(0.67)	(0.5, 0.67)	(0.67)
	A_5	(0.67)	(0.5)	(0.5)	(0.67)	(0.67)
R_{53}	A_1	(0.67, 0.75, 0.83)	(0.5, 0.67)	(0.5, 0.67)	(0.67)	(0.67)
	A_2	(0.5, 0.67)	(0.5)	(0.5)	(0.33, 0.5, 0.67)	(0.33, 0.5)
	A_3	(0.67)	(0.67)	(0.5, 0.67)	(0.5, 0.67)	(0.67, 0.75, 0.83)
	A_4	(0.67, 0.75, 0.83)	(0.83)	(0.67)	(0.5, 0.67, 0.83)	(0.83)
	A_5	(0.67)	(0.67, 0.75, 0.83)	(0.67, 0.75, 0.83)	(0.83)	(0.67)
R_{63}	A_1	(0.33, 0.5)	(0.33)	(0.33, 0.5, 0.67)	(0.5)	(0.33, 0.5)
	A_2	(0.5)	(0.5)	(0.5)	(0.33, 0.5)	(0.33, 0.5)
	A_3	(0.33)	(0.5)	(0.5)	(0.33)	(0.33, 0.5)
	A_4	(0.5, 0.67)	(0.5)	(0.5)	(0.5, 0.67)	(0.33, 0.5, 0.67)
	A_5	(0.67)	(0.5)	(0.67)	(0.5, 0.67)	(0.5)
R_{73}	A_1	(0.67, 0.75, 0.83)	(0.67)	(0.5, 0.67)	(0.5, 0.67, 0.83)	(0.5)
	A_2	(0.33, 0.5)	(0.5)	(0.5)	(0.33, 0.5, 0.67)	(0.5)
	A_3	(0.5, 0.67)	(0.5)	(0.5, 0.67)	(0.67)	(0.5)
	A_4	(0.5, 0.67)	(0.67)	(0.83)	(0.5, 0.67, 0.83)	(0.5, 0.67)
	A_5	(0.67)	(0.5, 0.67)	(0.5)	(0.5, 0.67)	(0.5)
R_{81}	A_1	(0.67, 0.75, 0.83)	(0.67, 0.75, 0.83)	(0.67)	(0.83)	(0.67)
	A_2	(0.5)	(0.5)	(0.5)	(0.33, 0.5, 0.67)	(0.5)
	A_3	(0.5, 0.67)	(0.5, 0.67)	(0.5, 0.67)	(0.67)	(0.5)
	A_4	(0.67, 0.75, 0.83)	(0.67, 0.75, 0.83)	(0.83)	(0.67)	(0.5, 0.67, 0.83)
	A_5	(0.5, 0.67)	(0.5, 0.67, 0.83)	(0.5)	(0.67)	(0.5)

$\{R_b\} = \{R_j\} - \{R_c\}$. After indicator separation, the Manhattan distance was applied to $d\left(\tilde{g}_{ij}, \tilde{g}_j^+\right)$, $d\left(g_{ij}, g_j^+\right)$, $d\left(\tilde{g}^+, \tilde{g}_j^-\right)$, and $d\left(g^+, g_j^-\right)$.

$$d\left(\tilde{g}_{ij}, \tilde{g}_j^+\right) = \frac{1}{L}\sum_{l=1}^{L} |\widetilde{g}_{ij}^{\,l} - \widetilde{g}_j^{+l}|, j \in J_H; d\left(g_{ij}, g_j^+\right) = |g_{ij} - g_j^+|, j \in J_C. \quad (23)$$

Applying Eq.21 and 22, the group utility (S_i = {0.521, 0.4927, 0.572, 0.5288, 0.4523}) and the individual regret (R_i = {0.0724, 0.0722, 0.0745, 0.0677, 0.0629}) were determined for each city, from which it was found that Nanjing (A_5) had the largest group utility and the smallest individual regret. Finally, without a loss of generality, ν was set at 0.5 and the VIKOR index Q_i was solved (Table 7). As the difference between the two smallest Q_i was 0.527, which was larger than 0.25, both *Condition* 1 and *Condition* 2 were satisfied. Nanjing (A_5) was the compromise solution with the highest urban flood resilience capacity.

According to the results, $Q_5 < Q_4 < Q_2 < Q_1 < Q_3$, the priority order of urban flood resilience is $A_5 < A_4 < A_2 < A_1 < A_3$. To verify if A_5 is the compromise solution, calculate $Q_4 - Q_5 = 0.527 > \frac{1}{m-1} = 0.25$, which satisfies two conditions simultaneously. Therefore, Nanjing had the highest urban flood resilience capacity.

4.3. Interpretation of results and sensitivity analysis

As shown in Table 7, if ν is 0.5, there is no difference between the utility and regret values for the decision makers. The result of Q_i is 0.6959, 0.57, 1, 0.5269, 0, for Guangzhou, Fuzhou, Ningbo, Shanghai and Nanjing, respectively. The urban flood resilience system of Nanjing is higher than the other four cities. Based on the VIKOR index Q_i, the rankings of the urban flood resilience from the high level to the low level are Nanjing, Shanghai, Fuzhou, Guangzhou and Ningbo, respectively. If ν is 0, only R_i affects the Q_i. Through this way, the managers can obtain the specific criteria to improve the urban flood resilience level. For example, according to Table 8 and R_i in Table 7, the medical capacity (R_{51}) needs to be improved for these cities, and the

Table 4
Experts' judgements to criteria importance after attitude-neutral extension.

R_{ij}	$f_{1,ij}$	$f_{2,ij}$	$f_{3,ij}$	$f_{4,ij}$	$f_{5,ij}$
R_{11}	(0.33,0.33,0.33)	(0.33,0.415,0.5)	(0.33,0.33,0.33)	(0.5,0.5,0.5)	(0.33,0.415,0.5)
R_{12}	(0,0.17,0.33)	(0.33,0.33,0.33)	(0,0,0)	(0,0.17,0.33)	(0.33,0.415,0.5)
R_{13}	(0.33,0.33,0.33)	(0,0.17,0.33)	(0,0.17,0.33)	(0.33,0.33,0.33)	(0,0.17,0.33)
R_{14}	(0.33,0.415,0.5)	(0.5,0.5,0.5)	(0.3,0.415,0.5)	(0,0.17,0.33)	(0.33,0.33,0.33)
R_{21}	(0.67,0.75, 0.83)	(0.83,0.83,0.83)	(0.83,0.915,1)	(1,1,1)	(1,1,1)
R_{22}	(0.83,0.83,0.83)	(0.83,0.915,1)	(1,1,1)	(0.83,0.915,1)	(0.83,0.915,1)
R_{31}	(0.67,0.75,0.83)	(0.83,0.83,0.83)	(0.67,0.75,0.83)	(0.83,0.915,1)	(1,1,1)
R_{41}	(0.5,0.5,0.5)	(0.5,0.585,0.67)	(0.33,0.5,0.67)	(0.83,0.83,0.83)	(0.5,0.67, 0.83)
R_{42}	(0.5,0.67,0.83)	(1,1,1)	(0.83,0.83,0.83)	(0.5,0.67,0.83)	(0.83,0.83,0.83)
R_{43}	(0.83,0.915,1)	(0.83,0.83,0.83)	(0.83,0.915,1)	(1,1,1)	(0.83,0.83,0.83)
R_{51}	(0.83,0.83,0.83)	(1,1,1)	(0.83,0.915,1)	(0.83,0.915,1)	(1,1,1)
R_{52}	(0.83,0.83,0.83)	(0.67,0.83,1)	(0.67,0.75,0.83)	(0.83,0.915,1)	(0.67,0.83,1)
R_{53}	(0.67,0.83,1)	(0.83,0.83,0.83)	(1,1,1)	(0.83,0.915,1)	(0.83,0.83,0.83)
R_{61}	(0.5,0.67,0.83)	(0.33,0.415,0.5)	(0.5,0.5,0.5)	(0.5,0.585,0.67)	(0.33,0.415,0.5)
R_{62}	(0.33,0.415,0.5)	(0.5,0.5,0.5)	(0.5,0.585,0.67)	(0.67,0.75,0.83)	(0.33,0.415,0.5)
R_{63}	(0.5,0.5,0.5)	(0.5,0.67,0.83)	(0.5,0.585,0.67)	(0.33,0.415,0.5)	(0.33,0.33,0.33)
R_{71}	(0.67,0.75,0.83)	(0.5,0.5,0.5)	(0.5,0.585,0.67)	(0.5,0.585,0.67)	(0.67,0.67,0.67)
R_{72}	(0.83,0.915,1)	(1,1,1)	(0.5,0.67,0.83)	(0.67,0.75,0.83)	(1,1,1)
R_{73}	(0,0.17,0.33)	(0,0.17,0.33)	(0.33,0.33,0.33)	(0.33,0.415,0.5)	(0,0,0)
R_{81}	(0.83,0.915,1)	(0.67,0.83,1)	(1,1,1)	(0.83,0.83,0.83)	(0.83,0.915,1)

employment equity (R_{73}) does not need much improvement for these cities. Although Nanjing has the highest level of the urban flood resilience, the rate of the children and old people needs to be decreased, and their self-rescue ability needs to be forced.

In the proposed method, the weight to the strategy of the maximum group utility, ν, is from 0 to 1. The sensitivity analysis considers different ν values, and gets the Q_i of 5 alternatives as shown in Fig. 4. From the results, Nanjing (A_5) is ranked as the city with the highest urban flood resilience level whatever the value of ν is. Therefore, the obtained result is robust that Nanjing enjoys the highest flood resilience level. On the other hand, based on the trend of Q_i as ν changes, the analysis obtains how the rankings of different alternatives are affected by the decision makers' preference for the group utility and the individual regret. The results show that the rankings of Ningbo (A_3) and Nanjing (A_5) are not affected by the value of ν at all, which means the results of these two alternatives have both the maximum group utility and the minimum individual regret. The ranking results of A_5 and A_3 are robust. The ranking of Shanghai (A_4) decreases as the value of ν increases. This means the ranking of Shanghai (A_4) improves when the decision makers focus on the minimum individual regret. On the contrary, the rankings of Guangzhou (A_1) and Fuzhou (A_2) improve as the value of ν increases. Therefore, Guangzhou (A_1) and Fuzhou (A_2) enjoy higher rankings when the importance of the maximum group utility increases.

Table 6
Normalized decision matrix for.J_C.

N	R_{14}	R_{41}	R_{42}	R_{43}	R_{51}	R_{52}	R_{61}	R_{62}	R_{71}	R_{72}
A_1	0.44	0.47	0.47	0.41	0.68	0.02	0.29	0.44	0.71	0.34
A_2	0.51	0.43	0.5	0.51	0.33	0.65	0.49	0.33	0.28	0.71
A_3	0.39	0.46	0.42	0.46	0.32	0.27	0.45	0.42	0.34	0.51
A_4	0.41	0.44	0.36	0.42	0.38	0.46	0.54	0.58	0.39	0.11
A_5	0.48	0.44	0.47	0.42	0.43	0.54	0.43	0.42	0.4	0.33

4.4. Suggestions

Three integral problems and suggestions were identified in the research.

(1) Enhance the emergency training of vulnerable people. While these 5 cities have focused on the education and cultural construction to protect vulnerable groups, the emergency capacity of these groups has been generally neglected. On average, around 20% of the population is either under 15 years of age or over 65%, with this rate being even higher in Ningbo and Fuzhou. Therefore, increasing their coping capacities could assist in improving overall urban flood resilience.
(2) Continue to expand the green infrastructure rate and repair the hydrological infrastructure. Both material resilience and integral network resilience are vital during flood operations; however, some

Table 5
Normalized decision matrix for.J_H.

N	R_{11}			R_{12}			R_{13}			R_{21}			R_{22}		
A_1	0.46	0.47	0.47	0.39	0.41	0.42	0.34	0.36	0.38	0.31	0.32	0.32	0.33	0.32	0.32
A_2	0.46	0.44	0.43	0.49	0.5	0.5	0.51	0.5	0.49	0.51	0.5	0.49	0.47	0.48	0.49
A_3	0.36	0.36	0.36	0.44	0.44	0.44	0.38	0.37	0.35	0.56	0.56	0.55	0.58	0.56	0.55
A_4	0.43	0.45	0.47	0.39	0.38	0.38	0.44	0.47	0.49	0.33	0.37	0.39	0.36	0.38	0.39
A_5	0.51	0.5	0.49	0.51	0.5	0.48	0.54	0.51	0.49	0.48	0.46	0.44	0.47	0.45	0.44
N	R_{31}			R_{53}			R_{63}			R_{73}			R_{81}		
A_1	0.44	0.47	0.48	0.44	0.44	0.44	0.36	0.39	0.42	0.47	0.48	0.49	0.53	0.52	0.5
A_2	0.42	0.43	0.44	0.31	0.34	0.36	0.43	0.42	0.42	0.36	0.37	0.37	0.35	0.35	0.35
A_3	0.39	0.39	0.39	0.44	0.44	0.44	0.4	0.38	0.36	0.44	0.43	0.42	0.41	0.41	0.42
A_4	0.47	0.48	0.49	0.51	0.51	0.5	0.46	0.49	0.51	0.5	0.51	0.51	0.51	0.52	0.52
A_5	0.5	0.47	0.44	0.51	0.5	0.48	0.56	0.53	0.51	0.44	0.43	0.42	0.41	0.41	0.42

Table 7
Results and comparisons.

Alternatives	Experts' weights with maximal consensus				Equal weights		TOPSIS	
	Q_i	Ranks	Q_i	Ranks	Q_i	Ranks	$\frac{S_i^-}{S_i^- + S_i^+}$	Ranks
A_1	0.6959	4	0.8177	4	0.6855	4	0.4574	3
A_2	0.57	3	0.8029	3	0.5935	3	0.386	4
A_3	1	5	1	5	1	5	0.3769	5
A_4	0.5269	2	0.415	2	0.5169	2	0.653	1
A_5	0	1	0	1	0	1	0.6141	2

Table 8
Scores of the individual regret.

R_{11}	R_{12}	R_{13}	R_{14}	R_{21}	R_{22}	R_{31}	R_{41}	R_{42}	R_{43}	R_{51}	R_{52}	R_{53}	R_{61}	R_{62}	R_{63}	R_{71}	R_{72}	R_{73}	R_{81}	
A_1	0.01	0.01	0.01	0.01	0.07	0.07	0.01	0	0.02	0.07	0	0.06	0.03	0.04	0.02	0.04	0	0.04	0	0
A_2	0.01	0	0	0	0.02	0.03	0.04	0.05	0	0	0.07	0	0.07	0.01	0.04	0.03	0.05	0	0.01	0.07
A_3	0.03	0.01	0.01	0.03	0	0	0.07	0.02	0.04	0.04	0.08	0.04	0.03	0.01	0.03	0.04	0.04	0.02	0.01	0.05
A_4	0.01	0.01	0	0.02	0.06	0.06	0	0.04	0.06	0.06	0.06	0.02	0	0	0	0.01	0.04	0.07	0	0.01
A_5	0	0	0	0.01	0.03	0.03	0.02	0.04	0.01	0.06	0.05	0.01	0	0.02	0.03	0	0.04	0.04	0.01	0.05

water conservancy departments have only paid attention to one of these, which has resulted in inefficiencies. Water conservancy bureaus need to ensure that the hydrological infrastructure is continually maintained and repaired before flood seasons, and that operational planning is implemented during floods. Greater focus also needs to be paid to the development of the sponge city concept when developing green infrastructure, which includes rooftops covered with plants, scenic wetlands for rainwater storage, and permeable pavements that store excess runoff water. However, even though these 5 cities have adopted some of these concepts, the flood resilience functions have been neglected; therefore, greater focus is needed to ensure that the green infrastructure is in good working order and can provide continual long-term protection.

(3) Increase the number of medical practitioners and hospitals. In the cities with high population density, the current medical capacities are too low to deal with the demand in a flood emergency. For example, there is a mismatch between the number of medical practitioners available at first-class Grade 3 hospitals in Guangzhou, increasing the rescue pressure on doctors. Continuous improvements in medical conditions are needed to eliminate this mismatch and improve flood resilience.

Based on the evaluation results, some specific suggestions for each city are given.

(1) As mentioned, Guangzhou needs to improve its medical conditions by putting greater capital investment into hospital construction. As Guangzhou has a higher economic capacity and a lower population density than the other cities, they have better recovery and adaptive capacities, better green infrastructure construction, and better floodgate maintenance.

(2) Fuzhou and Ningbo have high population densities. Resource integration and regional development could relieve the high population density pressure and also enhance the economic condition. Warning efficiency in Ningbo was found to be the highest of the 5 cities as it has focused more on floodgate maintenance. Therefore, Ningbo has a relatively higher pre-disaster resistance capacity. However, Ningbo needs to focus now on its coping capacity during floods to ensure there is a suitable balance between resource availability and population density.

(3) The urban flood resilience capacities in Shanghai and Nanjing were found to be similar. Although Shanghai had a better economic index and a lower population density, Nanjing had a higher level for both resource distribution and warning efficiency. The criteria weights indicated that the coping capacity during floods was the most important part of the urban flood resilience system. Therefore, the urban flood resilience in Nanjing was the highest. However, Shanghai had the highest adaptive capacity and highest recovery capacity of the 5 cities, but it needs to put greater focus on its

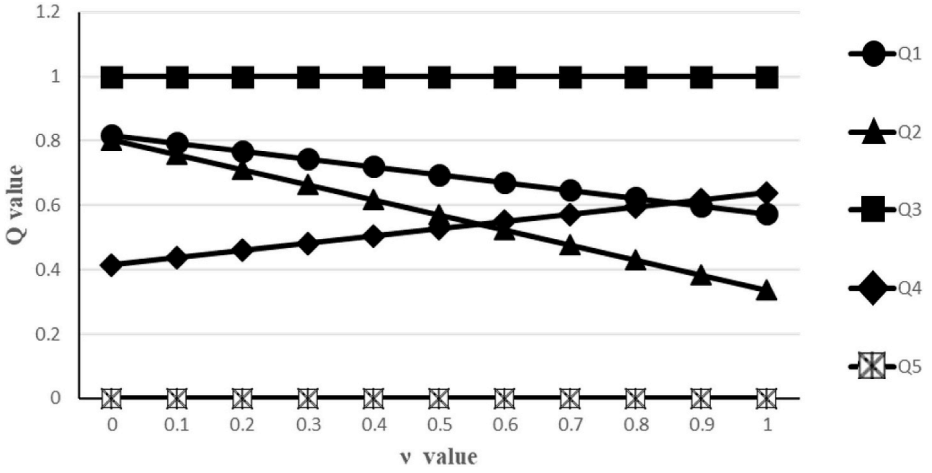

Fig. 4. Sensitivity results.

coping and resistance capacities, and especially needs to further develop the ecological environment, the hydrological infrastructure, and the warning capacity.

These suggestions adapt to these 5 cities based on the evaluation results. However, both the proposed urban flood resilience evaluation system and the proposed multi-criteria decision making method adapt to other regions. Managers in other cities can also apply this evaluation system to assess the urban flood resilience level and find specific criteria to improve.

4.5. Comparisons

This section compares the maximum consensus weights with the traditional equal weights, and also compares the proposed method with TOPSIS method.

When the experts' weights are equal, the weighted sum of the Euclidean distance from one expert's assessment scores to another's is 1.3558. When the experts' weights are from the maximum consensus model, the distance is remarkably decreased, and the group consensus becomes higher. The rankings by these two weighting methods are totally same (Table 7). Therefore, compared the traditional method, the maximum consensus model also obtains the effective results. In addition, the maximum consensus model achieves higher consensus than the equal weights method.

Then this paper ranks the alternatives by the TOPSIS method with the maximum consensus weights. From the results (Table 7), the ranking of A_3 from TOPSIS is the same with the ranking from the proposed method, while other alternatives' rankings change. The main reasons are the different characteristics of VIKOR and TOPSIS. First, to unify the units of criteria, VIKOR uses the linear normalization, while TOPSIS uses the vector normalization. Second, for TOPSIS, the smallest distance to the positive-ideal solution and the largest distance to the negative-ideal solution need to be achieved, whereas VIKOR uses the aggregation function of the distance to the ideal solution. Third, VIKOR considers the decision makers' preference between the group utility and individual regret by the parameter ν, which can lead to different ranking results.

5. Conclusion

The basic claim of this paper is that some urban floods are inevitable, it is essential to ensure urban flood resilience. The multi-criteria decision making method proposed in this paper provides a beneficial way to evaluate the condition of flood resilience for cities. In this way, some insights for increasing urban flood resilience are derived. The main contributions of this paper are: (1) an integrated comprehensive flood resilience evaluation indicator system was proposed that had hybrid information: crisp, random and hesitant fuzzy indicators for all phases of the disaster cycle; (2) the consideration of hesitant fuzziness in the urban flood resilience indicators increased the flexibility of the expert linguistic judgements; (3) the proposed weighting method was found to be able to achieve higher group consensus than traditional VIKOR methods with equal weights; (4) this paper extended the traditional VIKOR method to be able to deal with hybrid information; (5) practical managerial suggestions were put forward to increase urban flood resilience in 5 south-eastern coastal cities in P.R.China. The results showed the rankings for the 5 cities from the best alternative to the worst alternative were Nanjing, Shanghai, Fuzhou, Guangzhou, Ningbo, respectively. From the sensitivity analysis, the rankings of Nanjing and Ningbo were robust, and the rankings of other cities changed as the parameter ν changed. Despite the advantages of the proposed method, it also has some limitations that give the reference for future research. First, the weighting method can not describe the hesitancy degree, more advanced weighting methods can be applied. Second, from the sensitivity analysis, only two alternatives' ranking results were robust, while other alternatives' ranking results were fluctuate as ν changed. Methods to improve evaluation robustness can be studied in the future.

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Appendix A. Supplementary data

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